FORUM
Importance of Scientific Uncertainty in Decision Making

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ABSTRACT / Uncertainty in environmental decision making should not be thought of as a problem that is best ignored. In fact, as is illustrated in a simple example, we often informally make use of awareness of uncertainty by hedging decisions away from large losses. This hedging can be made explicit and formalized using the methods of decision analysis. While scientific uncertainty is undesirable, it can still be useful in environmental management as it provides a basis for the need to fund additional monitoring, experimentation, or information acquisition to improve the scientific basis for decisions.

Most environmental management decisions made with input from scientific analysis do not explicitly take into consideration the uncertainty in that analysis. For example, assessments of the impact of proposed wastewater treatment plants on receiving water quality typically involve deterministic simulation modeling and perhaps some judgmental consideration of uncertainty, but no formal uncertainty analysis. Likewise, the analysis of watershed land use on lake eutrophication is apt to involve simulation modeling but not uncertainty analysis (Reckhow 1985).

Why are simulation models, and scientific assessments, which are known to be uncertain, used for management decisions without consideration for the "goodness" (uncertainty) of the information? There probably are several reasons for this:

1. Limits on resources devoted to planning and analysis. Historically, agencies have not allocated funds, staff time, data collection effort, etc., to do more than a relatively quick analysis involving point estimates of response.
2. Lack of evidence that the current level of analysis is inadequate for the decisions. Despite the uncertainties, the decisions or designs implemented may still be satisfactory. Perhaps the system is insensitive to the uncertain quantities, or perhaps our measurements of system response are insensitive.
3. Lack of training in probability and statistics for the engineers who have developed many of the procedures used in making management decisions. Traditionally, most (but not all) environmental engineering curricula have emphasized deterministic analyses on engineered systems.
4. The engineer/scientist may feel that he/she will be perceived to be a failure as a professional if the true level of uncertainty is publicly acknowledged.
5. It may not be clear why a decision maker is better off knowing the level of scientific uncertainty.

The last reason is of particular importance, since a convincing explanation of the value of uncertainty analysis could make a difference with the other explanations as well (e.g., a key role for uncertainty in decision making could change agency priorities and engineering curricula). The following hypothetical example is offered to illustrate how we often informally take uncertainty into account in making decisions. This informal application of uncertainty is actually a good approximation for the formal use of uncertainty in decision theory.

Water Quality Standards: To Violate or Not To Violate

The manager of a industrial wastewater treatment plant is considering internal plant operation policies in response to a recently issued National Pollutant Discharge Elimination System (NPDES) permit. The NPDES permit stipulates that biochemical oxygen demand (BOD) should not exceed 2 mg/liter in the discharge from the plant. How should the manager operate the plant, or in other words, what should be the design BOD concentration in the wastewater discharge?

First, consider the situation in which engineering design and operation are perfect (without error). Can the plant manager specify the best operating policy

KEY WORDS: Uncertainty; Decision making; Decision analysis; Risk; Safety factors; Water quality management

under those conditions? The answer is no. To see this, consider first the situation where: (1) treatment cost decreases as BOD removal efficiency decreases, and (2) it is generally understood that there is no enforcement of the permit discharge limits as long as BOD concentrations are not greater than 1 mg/liter above the permitted level. Then, on economic arguments alone, the plant manager is likely to consider plant operation to achieve 3 mg/liter BOD (2 mg/liter + 1 mg/liter) in the effluent.

Alternatively, suppose: (1) treatment cost decreases (increases) as BOD removal efficiency decreases (increases) as before, and (2) one, even slight, violation of the permit limits results in the enforcement penalty of plant closure. In this case, the plant manager is likely to consider plant operation to achieve exactly 2 mg/liter BOD in the effluent (i.e., come as close as possible to the NPDES limit, but never exceed the limit).

It is apparent that in both situations, some notion of costs or losses was needed for the plant manager to justify a particular operating policy. Once stated, it probably seems obvious that the plant manager would request a cost analysis (including permit violation penalty costs) before deciding. Then, once the cost analysis is complete, the plant manager could implement the least-cost error-free operation. In summary, cost information was needed to supplement the water quality impact assessment, before the decision could be made.

What should the decision be if there is uncertainty in the engineering design and operation? To see how the interplay between scientific uncertainty and net cost should influence decision making, consider Figure 1. The bottom graph in Figure 1 presents the scientific and engineering assessments of BOD concentration in the treatment plant discharge. These assessments are presented as probability distributions, using probability as the expression of scientific uncertainty. The two bell-shaped curves in the bottom graph convey uncertainty through their dispersion (i.e., through how spread out they are). A third object in the bottom graph is a line with an upward-pointing arrow. This line/arrow represents the scenario described above—certain science; it is a probability density function with no width (no uncertainty) and infinite height.

In the upper graph of Figure 1, the lines represent costs (only costs above those required to exactly meet the NPDES permit requirements) in dollars, based on an NPDES effluent limit of 2 mg/liter. For simplicity, while not changing the central message presented

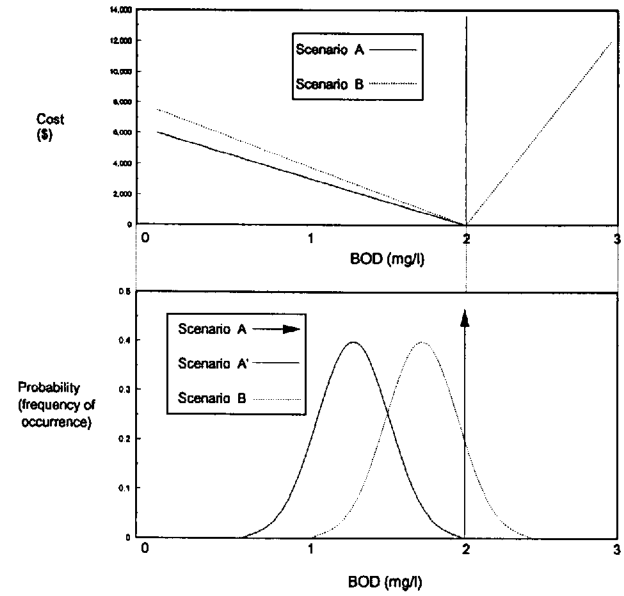

Figure 1. BOD concentration in the wastewater discharge: costs and probabilities of occurrence.

here, it is assumed that there are only two primary sources of costs: (1) penalty costs or fines associated with NPDES permit violations, and (2) costs that result from excess wastewater treatment, beyond that required to meet the permit limits. The height of the lines indicates the magnitude of the cost at a particular BOD discharge concentration. Thus, all lines drop to zero cost at exactly 2 mg/liter BOD, the point at which no fines are levied and treatment is not excessive. On either side of 2 mg/liter, the lines rise linearly, indicating a linear increase in cost associated with either: (1) fines for NPDES permit violations (above 2 mg/liter), or (2) excessive wastewater treatment (below 2 mg/liter). The vertical line just beyond 2 mg/liter represents an "infinite" fine for permit violation, which for the example above characterizes plant closure.

Two basic scenarios, A and B, are presented in Figure 1. Scenario A (solid lines on Figure 1) is the situation described above. In the lower graph, the scenario A arrow with no width indicates perfect scientific knowledge. In the upper graph, the scenario A cost function has infinite slope above 2 mg/liter, indicating that the discharger goes out of business. Below 2 mg/liter, the scenario A cost function linearly increases with decreasing BOD concentration, as a consequence of excessive treatment.

The two intertwined graphs in Figure 1 can be used to illustrate decision making under uncertainty in the following way. First, the cost function is determined (graphically and mathematically) and placed on the upper graph in Figure 1. Next, scientific and engineering knowledge concerning BOD discharge concentration should be characterized probabilistically and the probability distribution placed as a sliding overlay on Figure 1. The sliding overlay is meant as a graphical exercise to move horizontally and ultimately place the distribution of BOD discharge concentration such that expected cost is minimized.

Consider scenario A as an example. Scientific knowledge is certain, indicated by the arrow with zero width. The key management question is: given perfect knowledge, what should be the BOD discharge concentration (i.e., where along the BOD concentration scale should the arrow be placed) to minimize cost? Obviously, it should not be above 2 mg/liter, since the cost (penalty) is infinite. In addition, the further below 2 mg/liter the discharge is, the greater the cost of overtreatment. Thus, cost is minimized when the discharge concentration (and the arrow) is at precisely 2 mg/liter. In other words, with perfect knowledge and the asymmetric cost function (i.e., a different cost rate, in cost per milligram per liter BOD, associated with overtreatment from the 2 mg/liter NPDES limit versus that associated with undertreatment for scenario A) we should treat to just achieve the standard.

Given this understanding, we can now use the linked graphs to gain insight on decision making under scientific uncertainty. In the upper cost graph, again consider scenario A. Now, however, we acknowledge and quantify the scientific uncertainty inherent in the prediction of discharge concentration from a wastewater treatment plant. This uncertainty for the BOD discharge concentration is expressed in the probability distribution in the lower graph. As before, the probability distribution should be thought of as a horizontal sliding overlay that can be placed at any point along the horizontal axis. The optimal location for this sliding distribution is that which minimizes expected cost.

Where should this distribution of BOD discharge concentrations be placed (i.e., what should be the expected BOD concentration in the discharge to minimize expected cost)? Since cost is infinite if 2 mg/liter is exceeded, there must be no chance (zero probability) that BOD discharge concentration will be above 2 mg/liter. Thus, the distribution must be to the left of 2 mg/liter and must be far enough to the left so that no portion of the right tail exceeds 2 mg/liter (it is assumed that the probability distributions are symmetric and similar to normal density functions, except that the tails go to zero as displayed in Figure 1). The further to the left the BOD distribution is placed, the higher the cost of overtreatment. Thus, we do not want to place the distribution any further to the left than is necessary to avoid the infinite cost above 2 mg/liter. The solution is therefore clear—locate the BOD distribution so that the right tail intersects the horizontal axis (reaches zero probability) at exactly 2 mg/liter. This is identified as scenario A′ on the lower graph.

What can we learn from this example? First, note that in the absence of scientific uncertainty, we can discharge at the concentration limit (if costs justify this choice). However, once scientific uncertainty is considered (scenario A′ versus scenario A), discharging at the concentration limit may no longer be the optimal (least cost) choice (it is still optimal under certain specific conditions as noted below). Mathematically, the solution to this cost minimization problem involves the integration of the cost function with the probability model (Raiffa and Schlaifer 1968). This, in effect, weights the cost at each concentration increment by the probability that that concentration increment will occur in the discharge. Knowing that, we can see that the graphical representation of the solution must have zero probability above 2 mg/liter to negate the impact of infinite cost.

The final decision results from the fact that, in effect, we hedge decisions away from large (in this case, infinite) losses. This is a general strategy in decision making under uncertainty, whether it is based on formal scientific decision analysis (Raiffa 1968, von Winterfeldt and Edwards 1986) on informal, everyday decision making. As a consequence of hedging from large losses, note that the probability distribution is centered at BOD ~1.3 mg/liter; thus, the expected BOD concentration in the discharge is less than 2 mg/liter. The greater the dispersion (uncertainty) in the BOD probability distribution, the greater will be the difference between the NPDES limit and the expected discharge concentration. As this difference between expected discharge concentration and the permit limit increases, operating costs increase.

In general, reduction in scientific uncertainty should be expected to reduce the dispersion in the BOD distribution, which should result in management strategies that reduce operating cost. Of course, uncertainty reduction comes at a cost. In addition, the new knowledge associated with reduction in uncertainty may actually imply greater cost due to previously unforeseen consequences.

Once we understand the interplay between cost and uncertainty, the decision in scenario A′ is relatively simple because of the infinite cost of permit violation. The analysis becomes complicated with a more realistic cost function like that for scenario B in Figure 1. Yet, while we may not be able to precisely define the optimal solution to scenario B in a graphical sense, we can still gain some insight into the role of uncertainty by considering the general features of the solution.

Since the cost of NPDES permit violation is not infinite in scenario B, the optimal solution will now have a nonzero probability of standard violation, as long as the cost of overtreatment is greater than zero. The exact location of the sliding horizontal overlay distribution for scenario B can best be determined mathematically (by integration). However, it is clear that lower overall cost is achieved when the distribution is positioned allowing a small probability of permit violation cost (upper right tail), as opposed to a correspondingly small probability of higher unit cost of overtreatment (lower left tail). This is apparent when we note that the slope of the cost lines indicates the change in cost as BOD discharge concentration changes, and the height of the line at any point indicates the cost. Thus, the cost of extreme overtreatment (e.g., BOD discharge concentration of 0.5 mg/liter) is greater than the cost of a slight permit violation (e.g., BOD concentration of 2.1 mg/liter).

The proportion of the symmetric BOD distribution that exceeds 2 mg/liter is dependent on the relative slopes of the overtreatment and undertreatment cost functions. Some general conclusions are:

1. If the probablity distribution is symmetric, and the cost function is also symmetric (the slopes on the costs of overtreatment and undertreatment are identical), then the optimal solution will have an expected BOD discharge concentration of exactly 2 mg/liter (i.e., the distribution will be centered on 2 mg/liter).
2. If the probablity distribution is symmetric, but the cost function is asymmetric (the slopes on the costs of overtreatment and undertreatment are different), then the optimal solution will have an expected BOD discharge concentration on the side of 2 mg/liter with the cost function of lesser slope.
3. If the probability distribution is asymmetric, the solution is more difficult to characterize and describe, since the expected value is no longer the "center of symmetry" for the distribution. However, if the cost function is symmetric, then the asymmetric probability distribution will have its peak (mode) on one side of 2 mg/liter and its "stretched-out" tail on the other side, in order to hedge away from the large loss associated with the elongated distribution tail.

Implications for Safety Factors

It is common practice in environmental quality standard setting for the protection of human health (e.g., US drinking water standards) to employ safety factors as a means of extra protection against the harmful agent. As typically used, a safety factor is an adjustment to the standard making the standard more stringent (i.e., less harmful to human health), due to concern for scientific uncertainty. For example, the following multiplicative safety factors have been used in the establishment of drinking water standards in the US (De Zuane 1990, p. 51): 0.100 when good acute or chronic human exposure data are available and supported by acute and chronic data on other species; 0.010 when good acute or chronic data are available for one species, but human data are not; and 0.001 when acute and chronic data in all species are limited and incomplete.

How might we view safety factors in the context of the discussion in the previous section? To examine this issue, consider an example of the recommended drinking water standard for a noncarcinogenic synthetic organic compound (SOC). For this situation, the probability distribution in Figure 1 reflects the uncertainty in the human health effect of concern due to ingestion of the SOC, and the cost function reflects the cost of water treatment (which is largely responsible for the increasing cost at lower concentrations) and the human health cost (which is largely responsible for the increasing cost at higher concentrations).

The safety factors listed above reduce the standard concentration by 1–3 orders of magnitude, hedging in the direction of a more stringent standard for the SOC. How might this same effect be accomplished, not with a multiplicative factor, but with the analytic tools in Figure 1? As noted above, hedging may result from asymmetry in the probability distribution reflecting scientific uncertainty or asymmetry in the cost function or both. Since the safety factor is usually imposed because of poor scientific understanding (in this case, quality of the data on exposure), it is unlikely that scientific understanding allows discrimination between symmetry and asymmetry in the probability model. Further, since we know that the safety factor is intended to provide additional protection of human health, it is reasonable to consider the safety factor as an analog for the cost function associated with human health.

In that context, we could achieve the same effect as that from the use of the safety factor by adjusting the relative slopes of the costs of overtreatment and undertreatment. To be specific, under scientific uncertainty, if the slope of the cost function associated with a too lax (high) standard is greater than the slope of the cost function associated with a too stringent standard, then the probability distribution (assumed symmetric) will be hedged in the direction of more stringent standards. The distance that the distribution is shifted toward more stringent standards (toward the left) is a function of the relative slopes and the dispersion (uncertainty) in the estimate of human health effects.

Thus, implicit in the existence of a safety factor is an asymmetric cost function with human health costs rising more steeply than do overtreatment costs. Implicit in the magnitude of a safety factor are/is: (1) high uncertainty in human health impacts as represented in a probability distribution with substantial dispersion, and/or (2) a much steeper cost function for human health effects (undertreatment) than that for overtreatment. At issue, of course, is that these key points are implicit in the safety factors approach, and explicit in a decision analytic approach involving uncertainty.

In summary, comparing safety factors and conventional decision analysis:

1. The decision analytic approach maintains the separation of the science from the values (costs) throughout the analysis. This allows decision makers and observers of the decision process to understand the basis for decision (i.e., Was the uncertainty large? Were the costs of overtreatment much greater than the costs of undertreatment?). This, in turn, is compatible with follow-up work, such as proposals to reduce scientific uncertainty.

2. The use of safety factors obscures the real issues and areas of knowledge and uncertainty. The result can be be misuse of conclusions by a decision maker who does not understand the basis of the analysis (Raiffa 1982).

Conclusions

We have discussed and demonstrated the fact that one of the advantages of explicit consideration of uncertainty in environmental decision analysis is that it furnishes the basis for the often-prudent strategy of hedging away from large losses (see Morgan and Henrion 1990, for discussion of this and other related issues). Beyond that, in providing an estimate of how well we know the value of an important quality, uncertainty and decision analysis also indicate: (1) what aspects of the analysis are most uncertain, and (2) which uncertainties are most apt to affect the decision (decision-sensitive). Results from study of these two issues should be used to determine if it is wise to acquire more information before a decision is made.

With respect to the safety factor approach to scientific uncertainty, an argument that is naively made in support of environmental safety factors is that "we can never be too safe when human health is concerned." While no one can argue with the importance of human health, it is clearly unrealistic to require that human health be protected at all costs in all situations where human health is affected. Thomas (1972) presents a particularly effective example explaining the reasoning in support of nonzero risk standards for environmental contaminants. Acknowledging nonzero risk, Thomas proposes that standards achieve consistency across sectors of regulation. That is, for a particular human health effect (e.g., death or an injury of a specific type), resources allocated to avoid that effect in, for example, airline safety, should be roughly the same as the resources allocated for avoidance of that some effect in highway safety or public drinking water safety (if appropriate). This is an interesting idea that may be difficult to implement, yet it underscores the interconnection of public sector decisions and limited resources.

Even if we cannot implement the Thomas proposal, and even if time and resources prevent further investigation to reduce uncertainty, we can still expect that knowledge of uncertainty will lead to better decisions in the long run than will ignorance of uncertainty. We act on this fact in our everyday decisions by hedging, in essentially the same manner as we illustrated more formally in the hypothetical example presented above. Experiences like these and the recent emphasis on ecological risk assessment (see Bartell and others 1992, Suter 1993) may be expected to result in a greater role for uncertainty in environmental management.

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